

# Customer Behaviour Analysis

## 1. Project Overview

This project focuses on analyzing customer purchasing behaviour to understand buying patterns and preferences. The dataset was cleaned and transformed using Python to ensure accuracy and consistency. Power BI was used to create interactive dashboards for visual analysis. The analysis helps identify trends related to age group, gender, product categories, and spending behaviour. These insights can support better business decision-making and customer targeting strategies.

## Exploratory Data Analysis using Python

We began with data preparation and cleaning in Python:

- Data Loading: Imported the dataset using pandas.

```
df = pd.read_csv("C:/Users/Simran/Downloads/jupyter_notebook/Customer Shopping Analysis/customer_shopping_behaviour.csv")  
df.head(5)
```

|   | customer_id | age | gender | item_purchased | category    | purchase_amount | location  | size | color    | season | ... | subscription_status | shipping_type  | discount_appl   |
|---|-------------|-----|--------|----------------|-------------|-----------------|-----------|------|----------|--------|-----|---------------------|----------------|---|
| 0 | 2093        | 42  | Male   | Sandals        | Footwear    | 45              | Minnesota | M    | Silver   | Fall   | ... | No                  | Next Day Air   |   |
| 1 | 1117        | 67  | Male   | Backpack       | Accessories | 96              | Hawaii    | M    | Charcoal | Winter | ... | No                  | Express        |   |
| 2 | 953         | 36  | Male   | Hat            | Accessories | 71              | Idaho     | S    | Red      | Fall   | ... | Yes                 | 2-Day Shipping |   |
| 3 | 1528        | 26  | Male   | Hat            | Accessories | 75              | Wisconsin | L    | Red      | Fall   | ... | No                  | 2-Day Shipping | Activate Windows<br>Go to Settings to activate Windows. |
| 4 | 2483        | 69  | Male   | Handbag        | Accessories | 87              | Arizona   | S    | Peach    | Winter | ... | No                  | Next Day Air   |   |

- Initial Exploration: Used df.info() to check structure and .describe() for summary statistics.

```

#   Column           Non-Null Count Dtype  
--- 
0   customer_id    3900 non-null   int64  
1   age             3900 non-null   int64  
2   gender          3900 non-null   object  
3   item_purchased 3900 non-null   object  
4   category        3900 non-null   object  
5   purchase_amount 3900 non-null   int64  
6   location         3900 non-null   object  
7   size             3900 non-null   object  
8   color            3900 non-null   object  
9   season           3900 non-null   object  
10  review_rating    3900 non-null   float64 
11  subscription_status 3900 non-null   object  
12  shipping_type    3900 non-null   object  
13  discount_applied 3900 non-null   object  
14  promo_code_used 3900 non-null   object  
15  previous_purchases 3900 non-null   int64  
16  payment_method    3900 non-null   object  
17  frequency_of_purchases 3900 non-null   object  
18  date             3900 non-null   object  
19  age_group         3900 non-null   object  
20  purchase_frequency_days 3900 non-null   int64  
types: float64(1), int64(5), object(15)
emory usage: 640.0+ KB

```

|       | customer_id | age         | purchase_amount | review_rating | previous_purchases | purchase_frequency_days |
|-------|-------------|-------------|-----------------|---------------|--------------------|-------------------------|
| count | 3900.000000 | 3900.000000 | 3900.000000     | 3900.000000   | 3900.000000        | 3900.000000             |
| mean  | 1950.500000 | 44.068462   | 59.764359       | 3.750089      | 25.351538          | 89.133077               |
| std   | 1125.977353 | 15.207589   | 23.685392       | 0.713590      | 14.447125          | 119.037566              |
| min   | 1.000000    | 18.000000   | 20.000000       | 2.500000      | 1.000000           | 7.000000                |
| 25%   | 975.750000  | 31.000000   | 39.000000       | 3.100000      | 13.000000          | 14.000000               |
| 50%   | 1950.500000 | 44.000000   | 60.000000       | 3.760870      | 25.000000          | 30.000000               |
| 75%   | 2925.250000 | 57.000000   | 81.000000       | 4.400000      | 38.000000          | 90.000000               |
| max   | 3900.000000 | 70.000000   | 100.000000      | 5.000000      | 50.000000          | 365.000000              |

- Missing Data Handling:** Missing values in the `review_rating` column were handled using category-wise average ratings. If category averages were unavailable, the overall dataset average was used.  
This ensured no null values while maintaining meaningful customer insights
- Column Standardization:** Renamed columns to snake case for better readability and documentation.
- Feature Engineering:**
  - Created `age_group` column by binning customer ages.
  - Created `purchase_frequency_days` column from purchase data.

## ❖ Business Problem Statement

In today's competitive retail environment, understanding customer behavior is essential for improving profitability, retention, and long-term growth. The business currently collects large volumes of customer transaction data, but lacks a structured analytical approach to convert this data into meaningful business insights. The company is facing challenges in identifying:

- Which product category has consistent buying across all age groups?

2. Which month shows sudden spike in new customers?
3. Which age group has high purchase frequency but low spending amount?
4. Which product categories become less profitable when discounts are applied?
5. What factors (age, gender, or category) most strongly influence customer spending?
6. Which customer group should be targeted for premium memberships based on profitability and loyalty? Additionally, the business does not have clear visibility into:
7. Which age group is the most loyal even if their spending is low?
8. How does purchase frequency differ by age group and product category?
9. How do customer types differ in sales, behavior, and engagement?
10. Which customer group contributes most to subscriptions?

Without this understanding, the company risks inefficient marketing spend, poorly targeted promotions, ineffective discount strategies, and missed opportunities for customer lifetime value growth. Business Problem Statement

## Dashboard | Power BI





## 🔑 Key Insights & Findings

- The company is getting fewer new customers.
- Clothes category is being bought more by the young adults.
- The company has got 1053 subscribed customer.
- They are getting more sales from their loyal customers which is \$162690 and the average age of the loyal customers is 44.
- Although The company has 2721 loyal customers but only 759 customers have subscribed them.
- Most purchased product by loyal customer is jewelry.
- The company has got new customer in March and August and very less in October.
- Male gender is contributing more in sales than Female which is \$1,57,890.
- They have got more Young Adult age-group customer and in that 699 YA customers are loyal but Middle aged age-group has more subscribers.
- Each product is doing great after applying discounts.
- Sandle is Top rated product with 4.0 ratings and Bottom Rated Product is Short with 3.5 ratings

## Recommendations

- They Should focus more on promoting and Advertising their Company so that other people get to know about the company and they will get new customers.

- Also they should be giving monthly and seasonal discounts, this will attract more new customers as female customers are contributing less in sales so this will help.
- All the Categories are doing good after discount Applied so they can go with this strategy or they can give other discounts option to their customers.
- 2847 customers have not taken the subscription so they should add more values or offers in their subscription plan.
- loyal customers should be targeted for premium membership specially Young Adult age-group.